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Cross-market spillovers with 'volatility surprise'

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ARTICLE INFO

Article history: Received 12 November 2013 Accepted 11 August 2014 Available online 20 August 2014

JEL classification: C32 C4 G15

Keywords: Cross-market relationships Volatility surprise Volatility spillover ADCCX Asset management

1. Introduction

The study of volatility interaction is of interest to both academics and practitioners. Changes in variance are said to reflect the arrival of information, and the extent to which the market evaluates and assimilates new information.¹ The transmission pattern in variance provides an insight concerning the characteristics and dynamics of economic and financial prices, and such information can be used to construct better econometric models describing the temporal dynamics of the time series.

A rising research interest is directed toward the topic of international transmission mechanisms – attributable to the ever-increasing degree of interdependence among world financial markets – which seem to become more pronounced during financial crises. Regarding returns transmission, the study of *returns* co-movements begins with the investigation of the benefits from international diversification at various frequencies (Schwert (1989), Susmel and Engle (1994),

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ABSTRACT

This article adopts the asymmetric DCC with one exogenous variable (ADCCX) model developed by Vargas (2008), by updating the concept of 'volatility surprise' to capture cross-market relationships. Current methods for measuring spillovers do not focus on volatility interactions, and neglect cross-effects between the conditional variances. This paper aims to fill this gap. The dataset includes four aggregate indices representing equities, bonds, foreign exchange rates and commodities from 1983 to 2013. The results provide strong evidence of spill-over effects coming from the 'volatility surprise' component across markets. Against the background of the recent financial crisis, the aim is to contribute to the literature on the interdependencies of financial markets, both in conditional means and (co)variances. In addition, asset management implications are derived.

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Andersen and Bollerslev (1997)). Returns, volatility and correlation changes are closely related in financial models (Orlowski (2012), Bekiros (2013)).

Regarding volatility transmission, Ross (1989) shows that it is the *volatility* of an asset price, not the asset's price change, that is related to the rate of information flow to the market. This empirical justifies the study of international volatility transmission, in addition to returns contagion. Schwert, French, and Stambaugh (1987) and Campbell and Hentschel (1992) introduce the notion of the volatility feedback effect: volatility is typically higher after a stock market decrease than after it increases, which explains the negative correlation between stock returns and future volatility. In the same field, various studies examine the volatility spillover effects with univariate and multivariate GARCH models (Lin, Engle, and Ito (1994)). These models typically provide practical applications for optimal portfolio selection or option pricing (Al Janabi (2012), Konermann, Meinerding, and Sedova (2013)).

Let us now discuss the concept of volatility surprise. In finance, the attention is usually focused on the *predictable variance*, such as the conditional variance or the implied variance. However, according to Engle (1993), it is the difference that cannot be forecast between the squared residuals and the conditional variance that is worthy of interest. Such a quantity has been coined a 'volatility surprise'. Hamao, Masulis, and Ng (1990) were the first to interpret this quantity as a volatility surprise since it lags behind the conditional variance. This new concept paved the way for numerous studies (Kim and Rogers (1995), Chan-Lau and Ivaschenko (2003)).

¹ Ross (1989) shows that, in a no-arbitrage economy, the variance of price changes is directly related to the rate of information flow to the market. Engle et al. (1990) attribute movements in variance to the time required by market participants in processing new information.

Since the financial crisis of 2008, the topic of international volatility transmission across markets has once more attracted a considerable attention. Many researchers have concentrated on ways of measuring systematic risk, and spillovers have become a central issue. Some studies analyze the extent of cross-market linkages over different asset classes: stocks and bonds (Straetmans and Candelon (2013)), stocks and FX (Wang, Wu, and Lai (2013)), stocks-bonds-oil-gold and real estate markets (Chan, Treepongkaruna, Brooks, and Gray (2011)), metals and energy (Chng (2009)), gold and stocks (Hood and Malik (2013)), energy-food and gold (Mensi, Beljid, Boubaker, and Managi (2013)). Whereas the econometric methodologies sometimes differ from one study to another (e.g. DCC models or copulas), the global conclusion gears toward the frequent identification of cross-market links in recent empirical studies. Previous studies have mostly examined the spillovers in multivariate GARCH-type models (Engle, Ito, and Lin (1990), Hassan and Malik (2007), Cai, Howorka, and Wongswan (2008)), or with the BEKK VECM-GARCH model (Kavussanos, Visvikis, and Dimitrakopoulos (2014)).

In this paper, we contribute to the literature by proposing an alternative for modeling cross-market relations with multivariate volatility processes, on the basis of the asymmetric dynamic conditional correlation model with one exogenous variable (ADCCX) newly defined by Vargas (2008). This model represents a parsimonious specification for measuring cross-market relations. It is flexible in the sense that each market's shock may be fitted separately as a spillover on any combination of bivariate volatility models. Computationally, Vargas (2008) has established the consistency of the estimates in the presence of highdimensional optimization problems.

In contrast with previous works, this paper focuses on *volatility* interactions between equities, bonds, foreign exchange rates and commodities, as further evidence is emerging for volatility to be autocorrelated within its own market and also to be cross-correlated with volatility in other asset markets. As an extension to the work of Hamao et al. (1990), its key contribution is to document the spillover effects coming from each market's 'volatility surprise' component to the remaining pairs of covariance volatilities.² The two-step econometric methodology consists of (1) computing the mean-zero 'volatility surprise' component from univariate GARCH models, and (2) plugging it into the ADCCX model. As sensitivity tests, the performance of this technique is also examined during sub-periods.

To summarize our results, this paper aims to empirically model and measure volatility spillovers between four segments of the U.S. financial markets: stocks, bonds, commodities, and foreign exchange rates. The selected model is that of Vargas (2008), who presents an asymmetric dynamic conditional correlation model with exogenous variables in the covariance matrix's movement equation (ADCCX model). The main contribution of the paper consists in defining and calculating 'volatility surprises' for each market, and in asking whether a volatility surprise in one market affects the volatility of other markets (evaluated for each pair of assets). The paper finds evidence of volatility spillovers with, apparently, the stock markets being identified as the main source of volatility spillovers. By examining time-varying correlations, we are able to identify rising interdependencies between financial and commodity markets – pointing to the 'financialization of commodity markets' phenomenon (Tang and Xiong (2012)) – that are especially visible since 2008. This conclusion holds true for both volatility and return shocks.

The volatility risk transmission channel can well explain the theoretical underpinnings behind spillovers, whereby asset markets are interrelated through their dynamic conditional correlation structure. Our analysis greatly enhances the understanding of volatility crossmarket dynamics, both in turbulent and calm times. Besides, we attempt to build implications for asset managers. Finally, one central methodological contribution is brought to the attention of practitioners, related to the use of the 'volatility surprise' component (alongside other traditional measures of volatility) to apprehend fully the sensitivity of financial markets to volatility shocks.

The remainder of this paper is organized as follows. Section 2 contains a detailed description of the new methodology proposed. Section 3 outlines the data set. Section 4 contains the illustration with empirical results, along with a sensitivity analysis. Section 5 reflects on the implications in terms of asset management. Section 6 concludes.

2. The model

Vivid research areas in financial econometrics have attempted to model the time-varying volatility of financial returns. Indeed, capturing the time-varying correlations between different securities appears necessary for portfolio optimization, asset pricing and risk management. In this section, we outline the building blocks of this quest for modeling multivariate processes. The representation of the conditional covariance matrices adopted belongs to the DCC family.

2.1. The DCC family models

Multivariate GARCH (henceforth, MVGARCH) models are useful developments regarding the parameterization of conditional dependence. Different classes of MVGARCH models have been proposed in the literature.³ The first-generation models were introduced by Bollerslev, Engle, and Wooldridge (1988), as well as Engle and Kroner (1995). The numerical difficulties encountered with these models are linked to the large number of parameters to be estimated. Overparameterization will lead to a flat likelihood function, making statistical inference intrinsically difficult and computationally troublesome.

To overcome these difficulties, Bollerslev (1990) has proposed a new class of MVGARCH model in which the conditional correlations are constant (CCC). Even with such a simple specification, the estimation typically involves solving a high-dimensional optimization problem as, for example, the Gaussian likelihood function cannot be factorized into several lower dimensional functions.

The CCC assumption is relaxed by Engle (2002) and Tse and Tsui (2002), who generalize Bollerslev's (1990) model by making the conditional correlation matrix time-dependent. The dynamic conditional correlation (DCC) model constrains the time-varying conditional correlation matrix to be positive definite, and the number of parameters to grow linearly by following a two-step procedure. The first step fits each conditional variance with a univariate GARCH(1,1) model. The second step allows the computation of the dynamic conditional correlations given the conditional volatility estimated in the first step. The log-likelihood is therefore written as a sum of a volatility part and a correlation part. This two-step estimation procedure provides adequate fitting when the bivariate systems exhibit different dynamic correlation structures, and minimizes the biases that are inevitable in such an estimation strategy for the conditional correlation.

Cappiello, Engle, and Sheppard (2006) extend the DCC model to account for asymmetries in the correlation dynamics. Their asymmetric DCC (ADCC) model fits the leverage effects observed in equity markets

² Alternative econometric methodologies, to cite a few, include exploiting highfrequency data for improved (realized) covariance matrix measurement (Andersen, Bollerslev, Christoffersen, and Diebold (2007)), and the Multivariate Realized GARCH model (Hansen, Lunde, and Voev (2014)). The extension of these models to allowing one exogenous spillover variable between pairs of assets is left for future research.

³ One of the most general multivariate generalized auto-regressive conditional heteroskedasticity GARCH(p,q) models is the BEKK representation (Engle and Kroner (1995)). Although the form of this model is quite general, it suffers from overparameterization. Hence, we do not detail further BEKK-type models. For a survey, see Bauwens, Laurent, and Rombouts (2006).

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